

- HW 7 due Tues, Nov 26, 1pm

Recall: If X and Y are continuous RVs with joint PDF $f_{x,y}$ and marginals f_x and f_y , then the conditional PDF of

$$\textcircled{1} \quad X \text{ given } Y \text{ is } f_{x|y}(x|y) = \frac{f_{x,y}(x,y)}{f_y(y)},$$

$$\textcircled{2} \quad Y \text{ given } X \text{ is } f_{y|x}(y|x) = \frac{f_{x,y}(x,y)}{f_x(x)}.$$

Multiplication rule: $f_{x,y}(x,y) = f_{x|y}(x|y) f_y(y)$
 $= f_{y|x}(y|x) f_x(x).$

Ex 1: (Filtering)

- Cop using radar gun to detect speed.
Driver is going at speed $X \sim \text{Exp}(1)$,
- Given that actual speed is $X=x$,
radar gun shows a speed of $Y \sim N(x, \frac{x}{2})$.
- In other words, the "error" $Y-X$ is $N(0, \frac{x}{2})$
given $X=x$.
- Signal + error = $X + (Y-X) = Y$ = observed speed
- Typical goal in this kind of problem is to study
distribution of X given Y .
(Note we are given the distr. of Y given X .)

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Given

- $X \sim \text{Exp}(1) \rightarrow \text{PDF} \quad f_X(x) = \begin{cases} e^{-x} & \text{if } x \geq 0 \\ 0 & \text{if } x < 0. \end{cases}$

- $(Y|X=x) \sim N(x, \frac{x}{2})$

\rightarrow conditional PDF =

$$f_{Y|X}(y|x) = \frac{1}{\sqrt{\pi x}} e^{-\frac{(y-x)^2}{x}}$$

for $y \in \mathbb{R}$ and $x \geq 0$.

PDF of $N(\mu, \sigma^2)$

is $\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y-\mu)^2}{2\sigma^2}}$

for $y \in \mathbb{R}$

Thus, from multiplication rule, joint PDF is

$$\begin{aligned} f_{X,Y}(x,y) &= f_{Y|X}(y|x) f_X(x) \\ &= \begin{cases} \frac{1}{\sqrt{\pi x}} e^{-x - \frac{(y-x)^2}{x}} & \text{if } x \geq 0, y \in \mathbb{R} \\ 0 & \text{otherwise.} \end{cases} \end{aligned}$$

Bayes rule:

$$f_{X|Y}(x|y) = \frac{f_{X,Y}(x,y)}{f_Y(y)} = \frac{f_{Y|X}(y|x) f_X(x)}{f_Y(y)}$$

This gives us the PDF of X given $Y=y$, which is the distribution of true speed the driver given the reading on the radar gun.

Problem: What is f_Y ? (Only missing piece.)

$$f_Y(y) = \int_{-\infty}^{\infty} f_{X,Y}(x,y) dx = \int_0^{\infty} \frac{1}{\sqrt{\pi x}} e^{-x - \frac{(y-x)^2}{x}} dx$$

= ???

Conditional Expectation as a Random Variable

(a.k.a being systematic about conditioning)

We know if (X, Y) is discrete or continuous,
① ②

then

$$\textcircled{1} \quad E[X|Y=y] = \sum_x x p_{x|y}(x|y) \quad \text{where } p_{x|y}(x|y) = P(X=x|Y=y)$$

$$\textcircled{2} \quad E[X|Y=y] = \int_{-\infty}^{\infty} x f_{x|y}(x|y) dx \quad \text{where } f_{x|y} \text{ is conditional PDF.}$$

Law of total probability/expectation

$$\textcircled{1} \quad E[X] = \sum_y E[X|Y=y] p_y(y) = \sum_y g(y) p_y(y) = E[g(Y)]$$

$$\textcircled{2} \quad E[X] = \int_{-\infty}^{\infty} E[X|Y=y] f_y(y) dy = \int_{-\infty}^{\infty} g(y) f_y(y) dy = E[g(Y)]$$

↑
Proof:

Recall definitions:

$$E[X] = \int_{-\infty}^{\infty} x f_x(x) dx, \quad E[X|Y=y] = \int_{-\infty}^{\infty} x f_{x|y}(x|y) dx.$$

So

$$\int_{-\infty}^{\infty} E[X|Y=y] f_y(y) dy = \int_{-\infty}^{\infty} \left(\int_{-\infty}^{\infty} x f_{x|y}(x|y) dx \right) f_y(y) dy$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x f_{x|y}(x|y) f_y(y) dy dx$$

→ $f_{x,y}(x,y)$

$$= \int_{-\infty}^{\infty} x \int_{-\infty}^{\infty} f_{x,y}(x,y) dy dx$$

→ $f_x(x)$

$$= \int_{-\infty}^{\infty} x f_x(x) dx$$

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$$\begin{aligned}
 &= \int_{-\infty}^{\infty} x f_x(x) dx \\
 &= E[X]
 \end{aligned}$$

Definition: For each $y \in \mathbb{R}$ let $g(y) = E[X|Y=y]$.

Plug in the random variable Y , into this function $g: \mathbb{R} \rightarrow \mathbb{R}$, to get a new random variable $g(Y)$.

Notation: Write $E[X|Y]$ for this RV $g(Y)$.

No "y" in this notation

Note:

$$g(Y) \neq E[X|Y=Y] = E[X]$$

Tower property:

$$E[E[X|Y]] = E[X]$$

best guess for
 X after observing Y

best guess for
 X after observing Y

best guess of
the best guess...

More general versions... e.g.

$$E\left[E\left[E[X|Y,Z]|Y\right]\right] = E[X]$$

Ex 1 revisited:

We had $X \sim \text{Exp}(1)$ and $(Y|X=x) \sim N(x, \frac{x}{2})$.

Recall the mean of a $N(\mu, \sigma^2)$ random variable is μ .

Thus $E[Y|X=x] = x$ for all $x \in \mathbb{R}$.

Conditional expectation as a random variable:

Conditional expectation as a random variable:

$$E[Y|X] = X,$$

Tower property:

$$E[Y] = E[E[Y|X]] = E[X] = 1.$$

since $X \sim \text{Exp}(1)$

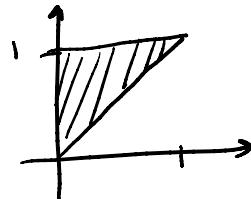
"Direct approach" would be

$$E[Y] = \int_{-\infty}^{\infty} y f_Y(y) dy$$

but we got stuck trying to compute f_Y before!

Ex 2: Suppose (X, Y) have joint PDF

$$f_{X,Y}(x,y) = \begin{cases} 8xy & \text{if } 0 \leq x \leq y \leq 1 \\ 0 & \text{otherwise,} \end{cases}$$



We found before:

$$f_Y(y) = \begin{cases} \int_{-\infty}^{\infty} f_{X,Y}(x,y) dx = \int_0^y 8xy dx = 4y^3 & \text{for } 0 \leq y \leq 1 \\ 0 & \text{otherwise.} \end{cases}$$

Conditional PDF of X given Y :

$$f_{X|Y}(x|y) = \frac{f_{X,Y}(x,y)}{f_Y(y)} = \frac{8xy}{4y^3} = \frac{2x}{y^2} \quad \text{for } 0 \leq x \leq y \leq 1.$$

Calculate: $E[X|Y=y] = \int_{-\infty}^{\infty} x f_{X|Y}(x|y) dx$

$$= \int_0^y x \cdot \frac{2x}{y^2} dx = \frac{1}{y^2} \left[\frac{2}{3} x^3 \right]_{x=0}^y$$

$$= \frac{2}{3} y, \quad \text{for each } 0 \leq y \leq 1.$$

Conditional expectation as a RV:

$$\mathbb{E}[X|Y] = \frac{2}{3}Y.$$

Tower property:

$$\begin{aligned}\mathbb{E}[X] &= \mathbb{E}[\mathbb{E}[X|Y]] = \mathbb{E}\left[\frac{2}{3}Y\right] = \frac{2}{3}\mathbb{E}[Y] \\ &= \frac{2}{3} \int_{-\infty}^{\infty} y f_Y(y) dy \\ &= \frac{2}{3} \int_0^1 y \cdot 4y^3 dy = \frac{2}{3} \cdot \left[\frac{4}{5}y^5 \right]_{y=0}^1 \\ &= \frac{8}{15}.\end{aligned}$$

"Direct method" would be to compute f_X first, then

$$\mathbb{E}[X] = \int_{-\infty}^{\infty} x f_X(x) dx = \dots \text{ would give } \frac{8}{15} \text{ also.}$$

This works just as easily here (no need for tower property).

Conditional Variance:

Last time we defined $\text{Var}(X|Y=y) = \mathbb{E}[X^2|Y=y] - (\mathbb{E}[X|Y=y])^2$.

Conditional Var as a RV is defined by

$$\begin{aligned}\text{Var}(X|Y) &= \mathbb{E}[X^2|Y] - (\mathbb{E}[X|Y])^2 \\ &= \mathbb{E}[(X - \mathbb{E}[X|Y])^2 | Y].\end{aligned}$$

exercise

Useful properties of $\mathbb{E}(X|Y)$: (Linearity)

$$① \quad \mathbb{E}[X + c(Y) | Y] = \mathbb{E}[X|Y] + c(Y)$$

$$\leadsto \mathbb{E}[c(Y)X|Y] = c(Y)\mathbb{E}[X|Y]$$

Recall:

$$\begin{aligned}\mathbb{E}[X+c] &= \mathbb{E}[X]+c \\ c\mathbb{E}[X] &= \mathbb{E}[cX]\end{aligned}$$

$$\textcircled{2} \quad E[c(Y)X|Y] = c(Y)E[X|Y]$$

for any RV $c(Y)$ depending only on Y .

$$\boxed{\begin{aligned} E[X+c] &= E[X]+c \\ E[cX] &= cE[X] \end{aligned}}$$

Law of total variance:

$$\text{Var}(X) = \underbrace{E[\text{Var}(X|Y)]}_{\substack{\text{unconditional}}} + \underbrace{\text{Var}(E[X|Y])}_{\substack{\text{conditional}}}$$

Proof:

$$\begin{aligned} E[\text{Var}(X|Y)] &= E[E[X^2|Y] - (E[X|Y])^2] \\ &= E[E[X^2|Y]] - E[(E[X|Y])^2] \\ &= \underbrace{E[X^2]}_{\substack{\text{tower property}}} - \underbrace{E[(E[X|Y])^2]}_{\substack{\text{linearity of } E}}. \end{aligned}$$

definition
of $\text{Var}(X|Y)$
linearity of E

$$\begin{aligned} \text{Var}(E[X|Y]) &= E[(E[X|Y])^2] - \underbrace{(E[E[X|Y]])^2}_{\substack{\text{definition} \\ \text{Var}(z)=E[z^2]-\langle z \rangle^2}} \\ &= \underbrace{E[(E[X|Y])^2]}_{\substack{\text{tower property}}} - (E[X])^2 \end{aligned}$$

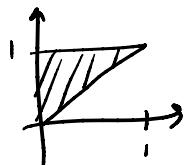
$\text{Var}(z)=E[z^2]-\langle z \rangle^2$

Adding these two, the **green terms** cancel out,

$$\begin{aligned} \text{so } E[\text{Var}(X|Y)] + \text{Var}(E[X|Y]) &= E[X^2] - (E[X])^2 \\ &= \text{Var}(X). \end{aligned}$$

Ex 2 revisited: $f_{X,Y}(x,y) = \begin{cases} 8xy & \text{if } 0 \leq x \leq y \leq 1 \\ 0 & \text{otherwise.} \end{cases}$

Found $f_{X|Y}(x|y) = \frac{2x}{y^2}$ for $0 \leq x \leq y \leq 1$,



$$\text{Found } f_{X|Y}(x|y) = \frac{2x}{y^2} \quad \text{for } 0 \leq x \leq y \leq 1,$$

$$\text{and } E[X|Y=y] = \frac{2}{3}y.$$

$$\begin{aligned}
 \text{Also } \mathbb{E}[X^2 | Y=y] &= \int_{-\infty}^{\infty} x^2 f_{X|Y}(x|y) dx \\
 &= \int_0^y x^2 \cdot \frac{2x}{y^2} dx \\
 &= \frac{1}{y^2} \left[\frac{1}{2} x^4 \right]_{x=0}^y \\
 &= \frac{1}{2} y^2.
 \end{aligned}$$

Thus $E[X|Y] = \frac{2}{3}Y$, and $E[X^2|Y] = \frac{1}{2}Y^2$;

$$\begin{aligned} \text{so } \text{Var}(X|Y) &= E[X^2|Y] - (E[X|Y])^2 \\ &= \frac{1}{2}Y^2 - \frac{4}{9}Y^2 \\ &= \frac{1}{18}Y^2. \end{aligned}$$

Law of total variance:

$$\begin{aligned}
 \text{Var}(X) &= E[\text{Var}(X|Y)] + \text{Var}(E[X|Y]) \\
 &= E\left[\frac{1}{18}Y^2\right] + \text{Var}\left(\frac{2}{3}Y\right) \\
 &= \frac{1}{18}E[Y^2] + \frac{4}{9}\text{Var}(Y) \\
 &= \frac{1}{18}E[Y^2] + \frac{4}{9}\left(E[Y^2] - (E[Y])^2\right) \\
 &= \left(\frac{1}{18} + \frac{4}{9}\right)E[Y^2] - \frac{4}{9}(E[Y])^2.
 \end{aligned}$$

Then find f_y and compute

$$E[Y^2] = \int_{-\infty}^{\infty} y^2 f_Y(y) dy \quad \text{and} \quad E[Y] = \int_{-\infty}^{\infty} y f_Y(y) dy$$

and plug this in to get $\text{Var}(X)$.

In this case, the "direct method" is probably easier,
to find f_X and use it to compute $\text{Var}(X)$ directly.
(Both give same answer.)